Ultrasonography and Electromyography based Hand Motion Intention Recognition for a Trans-radial Amputee: a Case Study

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Abstract

Surface electromyography (sEMG) has dominated upper-limb prosthesis control for decades due to its simplicity and effectiveness. However, the inherent variability of EMG signal hinders the flexible and accurate control of advanced multi-functional prosthesis. This study is an attempt to use ultrasonography (US) as an alternative for prosthetic hand control. A type of multi-sensory module, comprising a single-element ultrasound channel and one sEMG bipolar channel, is customised to ensure a fair comparison between these two modalities. Three machine-learning-oriented approaches were adopted to evaluate the performance in motion classification based on datasets captured from a trans-radial amputee. The experiment results demonstrated that the ultrasound outperformed the sEMG in random (98.9% vs 70.4%) and enhanced-trial-wise (74.10% vs 61.83%) cross-validation, but fell behind the sEMG in trial-wise (39.47% vs 58.04%) validation. This study preliminarily implies that 1) A-mode ultrasound signal can be more stable than the sEMG with minimum electrode shift, but more sensitive to external interference than the sEMG; and 2) to maintain high classification accuracy, US approach may require harsher electrode fixing mechanism or advanced on-line calibration approach.

Keywords: Ultrasonography, Electromyography, Upper-Limb Amputee, Prosthesis

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1. Introduction

Myoelectric upper-limb prosthesis has been commercialized in the past several decades. Multi-channel sEMG and pattern recognition have attracted great attention and achieved high classification accuracy in literature, however hardly to be applied clinical multi-functional prosthetic hand control due to its stability issues. sEMG is the measurement of potential discharged by muscles from skin surface, and thus it is rather difficult to use EMG signals to differentiate activities of overlapped muscle groups [1]. Additionally, sEMG is more likely to reflect extrinsic muscle contraction and less reflects intrinsic muscle activities. Thus, delicate prosthesis movement depending on precise measurement of intrinsic muscles is not achievable using sEMG only. Owing to the disadvantages of sEMG, recent studies are seeking new human machine interface (HMI) for prosthetic hand control. Fang *et al.* [2] surveyed a number of sensory technologies for intuitive prosthetic hand manipulation, among which ultrasound was summarized as an alternative solution for prosthetic hand control. US overcomes the inherent weakness of electromagnetic bio-signals, that can be easily contaminated by electronic interference.

Preliminary studies have demonstrated the possibility to leverage A/B-Mode to accurately trigger control of prosthetic hands, in terms of digit joint prediction [3, 4, 5, 6, 7, 8], finger tip force prediction[7, 9, 10], hand gesture classification [11, 12], and real-time virtual prosthetic hand control [13]. In 2014, Ravindra *et al.* [14] conducted a comprehensive comparison among sEMG, ultrasound imaging, and pressure sensing in a finger-flexion task, and led to a controversial conclusion that ultrasound imaging is not as acceptable as expected against its counterparts in terms of the prediction accuracy, the control stability, the wearability, and the cost. However, their data acquisition scenarios leave an unjustified condition for the comparative study of the two types of sensing techniques due to the difficulty of data capturing issues such as synchronization and transducer placement. Our previous study has compared them in able-bodied subjects [15, 16], and this study is a follow-up to compare them in a trans-radial amputee with more challenging situations, such as clinically acceptable electrode shift and elbow angles.

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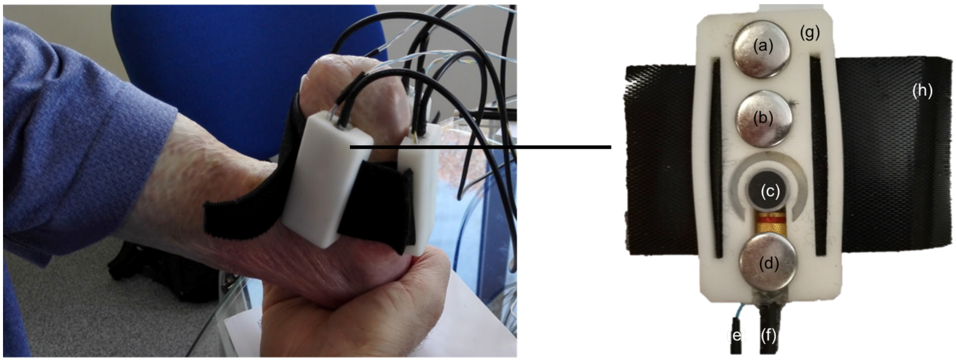

Figure 1: The experimental scenario, where four sensory ring comprising four sensory modules are fixed on remaining part of the forearm. The sensory module that integrates EMG electrodes and ultrasound transducer. (b) and (d) are the bipolar input electrodes and (a) is the reference electrode. (c) is the ultrasound transducer. (e) and (f) are the cables connecting the EMG device and ultrasound device. (h) is the velcro for connecting to other modules with adjustable angle. (g) is the container for all the mentioned elements.

2. Materials and Method

2.1. The Apparatus

A 16-channel EMG device, EMG100-Ch-Y-RA (Elonxi Ltd. UK) was used to measure the sEMG signal. The sampling frequency, ADC resolution and gain were 1 kHz, 24 bits and 24, respectively. A customised A-mode ultrasound device developed in our previous work [12] was used for signal capturing. The frequency of the transducer was 5 MHz and the sampling frequency was 10 fps.A single sensor module was specially designed for the amputee as shown in Fig. 1. The ultrasound transducer was located between two bi-polar EMG electrodes, which guarantees that the sensory information was measured from the same location of the body so as to achieve signal synchronization. A four-channel sensory ring was constructed for data collection based on the above-mentioned sensory module.

2.2. Data Collection

The data was captured in the rehabilitation clinical centre of ProActive Prosthetics Ltd. A male subject with trans-radial amputation was voluntarily involved in the experiment for data collection. The data collection procedure was approved by the Ethics Committee of University of Portsmouth. During data collection, the subject was informed to sit in a chair and put the elbow on the table in a comfortable posture, as seen in Fig. 1. The amputee was required to activate the residual muscles in the forearm to follow the hints showing on the screen with 9 hand gestures, including hand at rest (HR), hand close (HC), hand open (HO), index finger pointing (IFP), fine pinch (FP), wrist flexion (WF), wrist extension (WE), supination (SUP), and pronation (PRO). Two types of signal was capture simultaneously by a customised software. The subject conducted 20 trials in total. Every hint lasted 10 seconds, during which the amputee needed to respond to the hint, dynamically approaching the given motion, and maintained it until the hint disappeared. Between two hints, 10-second relaxing time was given. Re-wearing the sensors was required if the ultrasound signal disappeared due to the squeezing away of ultrasound gel. The recorded data was processed in Matlab R2018a.

2.3. Data Processing, feature extraction

2.3.1. EMG

The recorded sEMG signal was filtered by a 2^{nd} order high pass Butterworth filter with cutoff frequency at 20Hz to remover DC and cable artifacts. Root mean square (RMS), mean absolute value (MAV), wave length (WL), and the first four coefficients of autoregressive model (AR4) were extracted as the EMG features, which formed a 28-dimension feature vector. The window size and increments for feature extraction were 100 ms and 100 ms, which made the sampling frequency the same as the frame rate of ultrasound echo, *i.e.* 10 Hz. A 100 ms window size ensured that the captured information was constrained in the same sampling span.

2.3.2. Ultrasound

A 1D ultrasound signal was sampled at the frequency of 20 MHz with 997 valid sampling points, and the spatial resolution deep into body issue was 3.86×10^{-3} cm. The echo signal was pre-processed according to the procedure as published in our previous study [17], including the following four steps: time gain compensation, frequency filtering, envelope detection and log compression. A 15-dot-long window-sliding window without overlapping was applied to calculate two linear fitting coefficients (LFC), as the feature for classification. For each frame, a 392-dimension (4 channels, 49 LFC1 and LFC2 coefficients for each channel) feature vector was used for classification. Fig. 2 demonstrated the processing and extracted feature of a ultrasound signal.

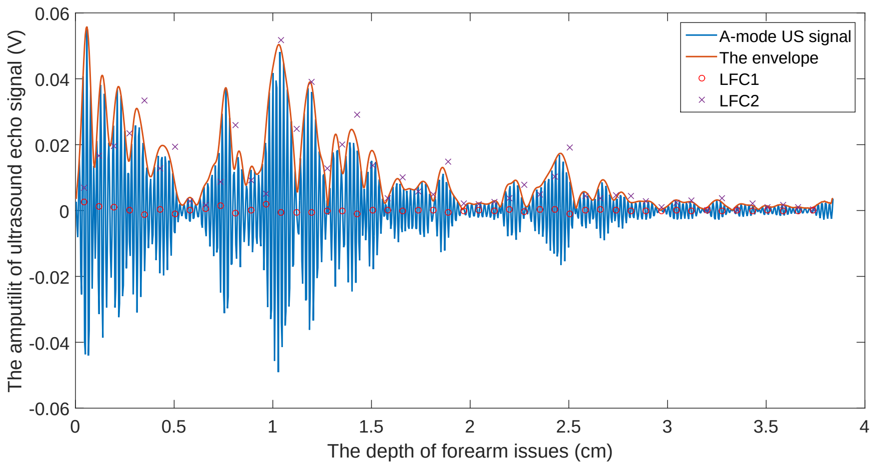

Figure 2: An instance of 1D US signal processing and the extracted features.

2.4. Evaluation approaches

A linear discriminate analysis based classifier was employed to classify the motions. Signals that obtained 5 second after each cue signal was used for classification. Three cross-validation strategies were included to compare the performance of sEMG and US, as listed below:

- **Random cross-evaluation test:** put all the observations from 20 trials into a pool (1000 observations in total), and randomly separated the pool into 10 folds, using one fold for testing and the rest for training. The algorithm was run 10 times to get the average accuracy.
- **Trial-wise cross-validation test:** use leave-one-trial-out strategy, which trained the classifier by nineteen out of twenty trials, and tested it by the remaining trial.
- **Enhanced trial-wise cross-validation test:** modify the trial-wise cross-evaluation test into a new version that train the classifier not only by nineteen out of twenty trials, but also one out of ten observations of the remaining trial.

3. Results

The average accuracy of the three experiment were displayed in Fig. 3. It was found that in random cross-validation test, US outperformed sEMG, while it was opposite in trial-wise

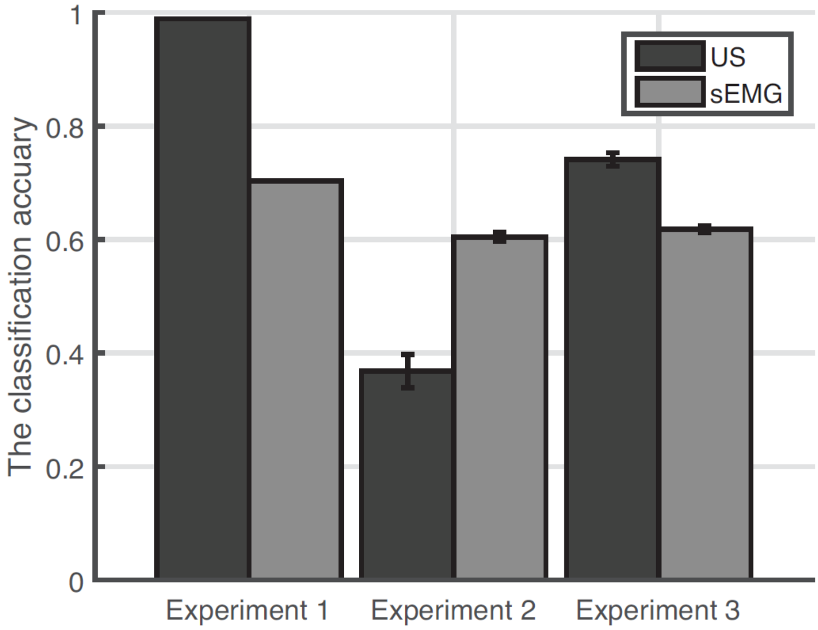

Figure 3: The overall comparison on experimental results.

cross-validation. But through including several samples from the remaining trial (*i.e.* enhance-trail-wise cross-validation), US can easily outperformed sEMG. In random cross-validation, the overall accuracy for US is $98.9 \pm 0.00\%$, while it was $70.4 \pm 0.06\%$ for sEMG. The overall accuracy was $39.47 \pm 1.7\%$ for US and $58.04 \pm 0.39\%$ for sEMG in trial-wise cross-validation. In the enhanced-trial-wise cross-validation test, the accuracy for US and sEMG were $74.10 \pm 1.20\%$, and $61.83 \pm 0.64\%$, respectively.

4. Discussion

4.1. Comparability

The experimental setup and data analysis methods took the comparability of these two muscle activity sensing approaches into account. Firstly, both sEMG electrode and US transducer are fixed into a rigid plastic container, and any physical movement of the container will affect both sEMG signal and US signal. There existed several studies for the comparison in different hand motion prediction tasks [14, 15, 18, 19, 20], among which most of them placed two types of electrode/transducer side by side. Secondly, the same number of channels was applied for US and sEMG data collection in a synchronous manner. Thirdly, the frame rate of 10 Hz was taken for both sEMG signal and US signal analysis.

4.2. Accuracy and Robustness

This study summarized the following three points in terms of accuracy and robustness for sEMG and US-based hand motion classification.

Firstly, this study achieved the accuracy above 95% for US-based hand gesture recognition in random cross-validation, which was comparable with other similar experimental results in [11, 15]. However, the sEMG-based one only reached the accuracy of around 70%. In the experiment, the classifier was trained by the data from all trials, and thus there were no unseen patterns for the classifier. This result implies that the US-based motion pattern can be very stable if the classifier was trained with sufficient data from all situations. Random cross-validation is far from the situation in practical prosthetic control, because it is hardly to keep the electrode exactly on the same position. This result proves the promising prospect of US for prosthetic hand control, with the evidence of distinguishing intended motions in a well-controlled experimental environment.

Secondly, trial-wise cross-validation test aims to evaluate the robustness of two sensing technologies, in which the testing data contained new variability that was unseen by the classifier in the training data. It was found that the US-based feature pattern under the same intended hand motions from different trials can be very different, reducing the accuracy dramatically. However, sEMG-based one would not be influenced so severely. This result implies that sEMG is more robust than US in a practical scenario, where electrode shift is inevitable, and the presentation of residual muscles of different motions may diverse among trials. This finding is consistent with the finding in [14].

Thirdly, enhanced trial-wise cross-validation test is to see the possibility whether a quick calibration can recover the classification performance, by means of adding a small portion of samples from the remaining trial. The experimental result demonstrated that quick calibration made a greater impact on US-based hand motion recognition than sEMG-based one, and it is more necessary for US-based system than sEMG-based one.

5. Conclusion

This study compared US and sEMG in hand motion intention recognition for a trans-radial amputee. We aimed to illustrate the pros and cons of both approaches and to direct future studies. A sensory module that integrated sEMG and ultrasound sensors was proposed to implement a feasible setup for comparison. Three machine-learning-oriented evaluation approaches were conducted for a comprehensive comparison in terms of accuracy, robustness and prospects. The results confirmed that US could achieve higher accuracy than sEMG in certain testing environment, but was more sensitive to artifacts, such as electrode shift, but a quick calibration could boost US' performance. Future studies will be conducted towards the challenges of minimization, transducer fixing strategy and avoiding the use of ultrasound gel.

Acknowledgement

The authors would like to thank Mr Alex Lewis who participated in data collection, and Mr. Wei Xia, Mr. Xingchen Yang and Mr. Xueli Sun for their assistance with hardware preparation, and to acknowledge the support from the EU Seventh Framework Programme (FP7)-ICT under Grant No. 611391, Natural Science Foundation of China under Grant No. 51575338 and 61733011.

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